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Design and Development of Brain Tumor Classification using Hybrid Deep Learning Algorithm

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ABSTRACT

Traditional brain tumor classification methods face limitations regarding time-consuming manual analysis and the potential for inaccuracies. The study proposes a novel approach for brain tumor classification using a hybrid deep learning model incorporating **U-Net** and **CNNs**. The model will be trained on a large dataset of labeled MRI images to learn features and classify tumors automatically. This approach promises faster diagnoses, improved accuracy compared to traditional methods, and reduced workload for radiologists. The research aims to explore the application of other imaging modalities and expand the scope of the tumor detection system.

KEYWORDS: *U-Net, Convolutional Neural Network, brain tumor, MRI scans*

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I. INTRODUCTION

Brain tumor classification, vital for effective treatment strategies, currently relies on time-consuming and often inaccurate manual methods. Deep learning has emerged as a promising alternative, and this paper introduces a novel approach using a hybrid deep learning model applied to MRI scans for automated and objective tumor classification. This model leverages the strengths of both U-Net, for its biomedical image segmentation prowess, and edge-based CNNs, for efficient real-time processing on resource-constrained devices. By combining these architectures, the aim is to achieve high accuracy and practical deployability, potentially leading to faster diagnoses, reduced radiologist workload, and overall improved patient outcomes through facilitated early intervention. The rest of the paper will detail the proposed methodology, evaluation, and the potential of this approach.

II. RELATED WORK

The authors in [1] proposed a CNN technique for a three-class classification to distinguish between three kinds of brain tumors, including glioma, meningioma, and pituitary tumors. They used a pre-trained GoogleNet for feature extraction from brain MRI scans. To identify the extracted features, proven-based classifications are used. The suggested approach outperforms existing approaches with an average classification accuracy of 98%.

ImageNet-based Vision Transformer (ViT) models (B/16, B/32, L/16, and L/32) that have been trained and fine-tuned were proposed by [2] for brain tumor

\classification purposes. Validation and testing were performed on a three-classes brain tumor dataset from Figshare that included 3064 T1w contrast-enhanced (CE) MRI slices with gliomas, meningiomas, and pituitary tumors. L/32 was the highest model, gaining

98.2% in the total test accuracy at a resolution of 384 × 384.

B. Srikanth et al. presented [3] a 16-layer VGG-16 deep NN, which accepts improved images from a prior pre-processing phase as input and moves them through the convolution layer for extracting the features and downsampling (Convolution, ReLU, MaxPooling). Their proposed approach increased the precision of brain tumor MR image multi-classification. To avoid the overfitting problem, completely linked and SoftMax layers are employed. Lastly, after 20 training iterations, their proposed model achieved the best outcomes, with 98 percent accuracy.

III. PROBLEM STATEMENT

Traditional methods for brain tumor classification, reliant on manual analysis by radiologists, suffer from significant limitations. These limitations include:

1. Time-consuming and labor-intensive manual analysis: Radiologists face a heavy workload and the risk of human error in visual examinations.
2. Potential for inaccuracies: Subjective interpretation of images can lead to misdiagnoses and impact treatment decisions.
3. Limited ability to handle complex image variations: Traditional methods may struggle to accurately classify tumors with subtle variations in appearance or complex morphologies.

This research aims to address these limitations by developing a novel approach for accurate and efficient brain tumor classification using a hybrid deep learning model.

IV. SOFTWARE REQUIREMENTS

Programming Language: Python

Libraries and Frameworks: TensorFlow/ PyTorch

Deep Learning Models/Architectures: U-Net and CNN

Development Environment: Google Colab / Jupyter Notebook

V. HARDWARE REQUIREMENTS

Processor: Minimum: Intel Core i5

Graphics Processing Unit (GPU): Minimum: NVIDIA GTX 1650 or higher.

Memory (RAM): Minimum: 8 GB.

Storage: Minimum: 500 GB HDD or SSD.

VI. PROPOSED SYSTEM

1. U-Net for Biomedical Image Segmentation:

We utilize the U-Net architecture [4][5][6] to effectively segment the tumor regions within the MRI scans. U-Net is specifically chosen for its proven ability to learn both context and details in medical images. It consists of convolutional and deconvolutional layers that enable the extraction of hierarchical features crucial for accurate segmentation. The architecture of U-Net helps to overcome the limitations of limited annotated data in the medical field and is known for maintaining a good balance between speed and accuracy. By using the U-Net architecture, we can obtain accurate tumor segmentation masks which serve as critical input to our subsequent classification steps.

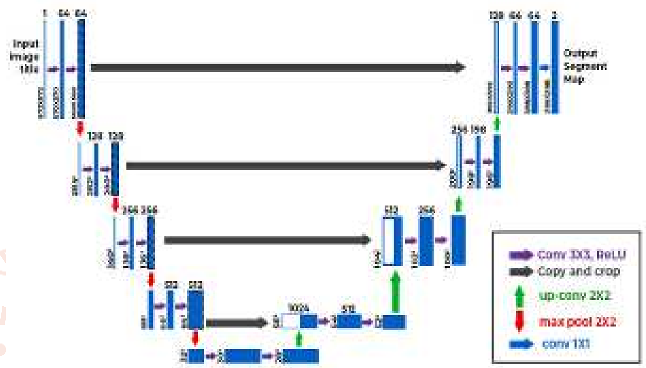

Fig1: U-NET Architecture

2. Edge-Based CNNs for Classification:

Following segmentation with the U-Net, we employ edge-based CNNs [7][8][9] for tumor classification. These CNNs are designed to operate on devices with limited computing resources, enabling efficient real-time analysis, and moving beyond the reliance on remote processing power. Edge-based CNNs are used here to analyze the segmented tumor regions and classify the tumors into distinct pathology categories. The primary benefit of the edge-based CNNs lies in their ability to process data at the source reducing latency and increasing privacy. This dual-stage process ensures accurate and computationally efficient classification.

3. Hybrid Architecture and Training:

The integrated architecture is trained end-to-end on a large dataset of labeled MRI images. This allows the model to automatically learn the most discriminative features for tumor classification, beyond traditional handcrafted features. By training the U-Net and edge-based CNN models simultaneously, we take advantage of the combined strengths of both models[10].

Complementary Strengths: U-Net excels at capturing the full context of the medical image (global perspective) and precisely delineating the tumor. Edge-based CNNs offer speed and efficiency, which is needed for real-time processing or use on local devices, bringing the ability to run analysis with minimal latency.

Problem Decomposition: A hybrid architecture essentially decomposes the complex task of brain tumor classification into sub-problems. U-Net can initially perform segmentation. Later edge edge-based CNN can classify.

Resource Constraints: Combining a U-Net with an edge-based model means that initial processing, particularly the resource-intensive segmentation task, can be handled separately, and then lighter-weight, edge-compatible models can work with these segmentations. This may also save resources if, for example, initial scans rule out any potential problems.

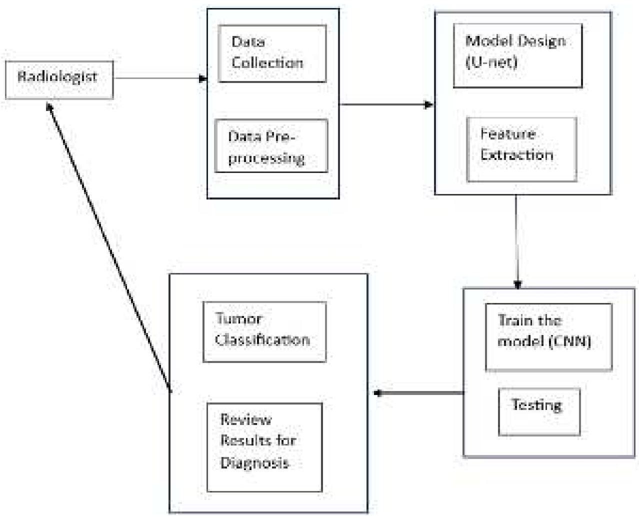

Fig2: Architecture Diagram

VII. RESULT

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Final Training Loss: 3.66%
Final Validation Loss: 3.00%
Final Training Accuracy: 98.70%
Final Validation Accuracy: 98.94%
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Fig2: Accuracy

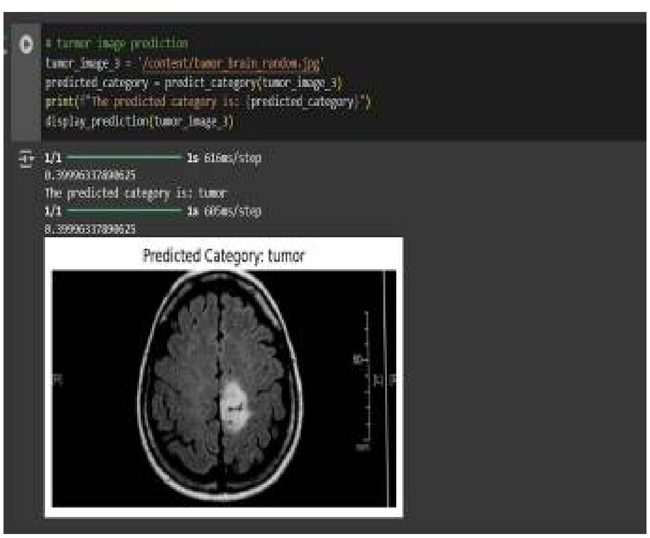

Fig4: Tumor Prediction

Fig5: No Tumor Prediction

VIII. CONCLUSION

This study successfully proposed a hybrid deep learning model combining U-Net and edge-based CNNs for brain tumor classification. The approach leverages the segmentation capabilities of U-Net with the efficiency of edge-based models, enabling real-time analysis on resource-constrained devices. This method offers improved accuracy and reduced workload for radiologists, potentially surpassing traditional techniques. Ultimately, this hybrid model has the potential to improve patient outcomes through faster and more precise diagnoses. Future work includes expanding to various imaging modalities to improve comprehensive tumor detection.

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